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Forest Ecology and Management 222 (2006) 191–201

Forest Ecology and Management

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Temporal evolution of carbon budgets of the Appalachian forests in the U.S. from 1972 to 2000

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Received 30 December 2004; received in revised form 27 September 2005; accepted 30 September 2005

Abstract

Estimating dynamic terrestrial ecosystem carbon (C) sources and sinks over large areas is difficult. The scaling of C sources and sinks from the field level to the regional level has been challenging due to the variations of climate, soil, vegetation, and disturbances. As part of an effort to estimate the spatial, temporal, and sectional dimensions of the United States C sources and sinks (the U.S. Carbon Trends Project), this study estimated the forest ecosystem C sequestration of the Appalachian region (186,000 km^2) for the period of 1972–2000 using the General Ensemble Biogeochemical Modeling System (GEMS) that has a strong capability of assimilating land use and land cover change (LUCC) data. On 82 sampling blocks in the Appalachian region, GEMS used sequential 60 m resolution land cover change maps to capture forest stand-replacing events and used forest inventory data to estimate non-stand-replacing changes. GEMS also used Monte Carlo approaches to deal with spatial scaling issues such as initialization of forest age and soil properties. Ensemble simulations were performed to incorporate the uncertainties of input data. Simulated results show that from 1972 to 2000 the net primary productivity (NPP), net ecosystem productivity (NEP), and net biome productivity (NBP) averaged 6.2 Mg C ha^{-1} y^{-1} (±1.1), 2.2 Mg C ha^{-1} y^{-1} (±0.6), and 1.8 Mg C ha^{-1} y^{-1} (±0.6), respectively. The inter-annual variability was driven mostly by climate. Detailed C budgets for the year 2000 were also calculated. Within a total 148,000 km^2 forested area, average forest ecosystem C density was estimated to be 186 Mg C ha^{-1} (±20), of which 98 Mg C ha^{-1} (±12) was in biomass and 88 Mg C ha^{-1} (±13) was in litter and soil. The total simulated C stock of the Appalachian forests was estimated to be 2751 Tg C (±296), including 1454 Tg C (±178) in living biomass and 1297 Tg C (±192) in litter and soil. The total net C sequestration (i.e. NBP) of the forest ecosystem in 2000 was estimated to be 19.5 Tg C y^{-1} (±6.8).

Keywords: Land cover change; Forest ecosystem; Carbon source and sink; Scaling; Model

1. Introduction

Terrestrial ecosystem carbon (C) sequestration can reduce the rate of build up of greenhouse gases in the atmosphere and therefore can contribute to a better human adaptation to current and future environmental changes. Forest ecosystem C sequestration is of particular interest to researchers and policy makers because, at global scales, forests account for 80–90% of terrestrial plant C and 30–40% of soil C (Landsberg and Gower, 1997; Harvey, 2000). Forests and forest soils have large capacities to both store and release C (Cannell et al., 1992; Dixon et al., 1994), and detailed forest ecosystem C budgets are helpful for improving our understanding of the terrestrial C cycle and for supporting the decision-making process in forest management. However, estimating large-scale forest ecosystem C budgets is complicated because of the difficulty of quantifying the impacts of both natural environmental variability and human disturbances. As a major indicator of human disturbances, land use and land cover change (LUCC) information, if available, needs to be incorporated into both retrospective and predictive C budget calculations. Although little has been done in temperate ecosystems, some research work that mainly focused on tropical ecosystems estimated that deforestation has been responsible for 87% of the estimated emissions due to land-use change since 1850 (Houghton, 1999; Houghton et al., 1999, 2000; IPCC, 2000). The global C

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doi:10.1016/j.foreco.2005.09.028

emission due to human-induced LUCC was about 1.6 ± 0.8 Pg C y^{-1} (1 Pg = 10^{15} g) in the 1990s, which was more than two times the magnitude of the net global C sequestration (0.7 ± 1.0 Pg C y^{-1}) during the same period (IPCC, 2000). Nevertheless, it has been a major challenge to detect and quantify the dynamic nature of LUCC over large areas (Loveland et al., 2002; Liu et al., 2004a). Due to the difficulties in mapping LUCC dynamics over large areas, consistent high-resolution spatial LUCC data are rarely available at the regional scale.

There exist generally three types of large-scale C estimation methods to incorporate historic LUCC information: (1) inventory-based methods with low spatial resolution LUCC data, (2) biogeochemical process-based methods with static or assumed LUCC history, and (3) biogeochemical process-based methods with high-resolution LUCC data. Inventory-based methods mainly use growth and yield data to estimate historic C stocks and C budgets, such as the United States C accounting by Turner et al. (1995) and the Canadian C accounting (CBM-CFS) by Kurz and Apps (1995, 1999). The direct tree measurements and the derived forest growth curves from inventory have laid a solid basis for this type of method and would enhance other methods. Land cover change histories (forest harvests and fire disturbances) were incorporated into the C accounting method, but usually were averaged to larger scale due to constraints of data and resources. Some concerns about this method include the transferability of forest growth curves across regions and the lack of data on belowground C components. High-resolution spatially explicit process-based methods mainly use physiological tree growth models and Geographic Information System (GIS) data. Examples include 3PG-SPATIAL (Landsberg and Waring, 1997), InTEC (Chen et al., 2000), Liu et al. (2005), and BGC-MODIS (Heinsch et al., 2003). These approaches try to incorporate more details of the varying environmental factors and provide more details of temporal trends and spatial distribution of C sequestration. Impacts of inter-annual climate variations and spatial soil property variances are commonly considered. These approaches are usually limited by the lack of a dynamic high-resolution LUCC datasets. They may use static land cover (vegetation cover) types or assume potential dynamic vegetation cover types that are driven by some natural forces such as climate change. Real land cover change history was incorporated into some of these models but was usually simplified. The LUCC-dependent C estimation methods often use reconstructed LUCC history data (Carter et al., 1993; Howard et al., 1995; Kelly et al., 1997; Parton and Rasmussen, 1994; Hurtt et al., 2002; Parton et al., 2004). These methods focus on dynamic LUCC impacts, and the LUCC data may come from various sources. This method has recently been extended to drive process-based ecosystem models over large areas, performing Monte Carlo initializations and ensemble model simulations by assimilating various observed or reconstructed high-resolution LUCC-related data, including sequential remote sensing-based land cover change maps, soil data, agricultural census data, and forest inventory data (Moorcroft et al., 2001; Liu et al., 2004a, 2004b).

Forest ecosystems in the United States might significantly contribute to the global C sink (Turner et al., 1995; Birdsey and Heath, 1995; Heath and Birdsey, 1993; Heath and Smith, 2000; Heath et al., 2002; Goodale et al., 2002). Nevertheless, large uncertainties remain regarding the spatial and temporal patterns and driving forces of the terrestrial C sink (Houghton et al., 1999; Ciais et al., 2000; Pacala et al., 2001; Hurtt et al., 2004; Liu et al., 2004a). The overarching goal of the U.S. Carbon Trends Project is to estimate the spatial and temporal change of C sequestration in the conterminous United States. This paper focuses on the magnitude and temporal C trends of the Appalachian forest ecosystems using the dynamic LUCC history. The LUCC in this study includes both permanent land cover type conversions (e.g. forest to urban) and temporary disturbances (e.g. forest cuttings and regenerations).

2. Sites and methods

2.1. The Appalachian region and LUCC sampling blocks

The Appalachian region is located in the eastern part of the United States covering parts of Pennsylvania, West Virginia, Virginia, Kentucky, North Carolina, Tennessee, Alabama, and Georgia. Our study area includes three of six Omernik level III ecoregions (Fig. 1): the Blue Ridge (BR), the Ridge and Valley (RV), and the Central Appalachians (CA). The North Central Appalachians, Southwest Appalachians, and Northern Appalachian Plateau and Upland ecoregions are not included at this time. The Appalachian forest, with an area of 186,000 km^2, is one of the most diverse assemblages of plants and animals found in the world's temperate zone. The BR and the CA ecoregions are about 80% forested. The RV ecoregion, an important crop production region, has about 56% forest cover. Almost all of the forest in these ecoregions is re-growth following cutting (Stephenson et al., 1993) or following agricultural abandonment.

For this study, ten 20 km $\times$ 20 km sampling blocks in the BR region and seventy-two 10 km $\times$ 10 km sampling blocks in the CA and RV regions were used for land cover change detection under the U.S. Land Cover Trends Project (Loveland et al., 2002). The original sampling design used 20 km $\times$ 20 km sampling blocks, and a revised design used 10 km $\times$ 10 km sampling blocks to better capture the spatial variability of LUCC. The land cover types within each sampling block were derived from five dates of the Landsat MSS, TM, and ETM+ data (nominally 1973, 1980, 1986, 1992, and 2000), which were analyzed at 60 m resolution. There are 10 land cover types defined: water, developed (urban), human disturbed, mining, natural barren, forest, grass and shrub, agricultural, wetland, and natural disturbed area. For the ecoregions in this study, the human disturbed land cover type represents forest clear cutting.

2.2. Overview of the General Ensemble Biogeochemical Modeling System (GEMS)

GEMS is designed for regional scale C modeling. The spatial simulation units of GEMS are the cases in a joint

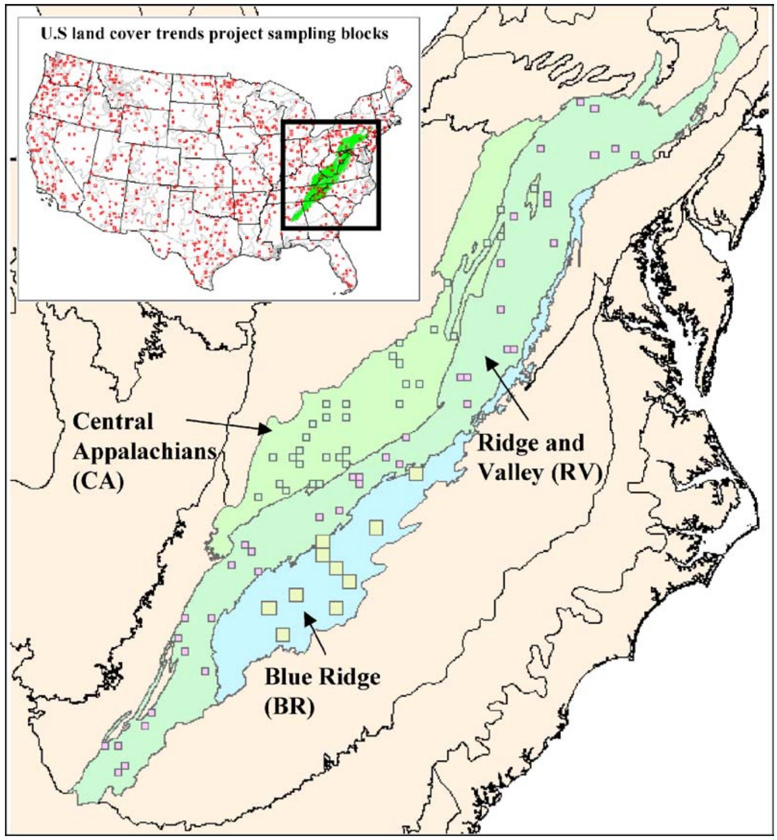

Fig. 1. Land cover change and GEMS carbon simulation sampling blocks in the Appalachian region. Sampling blocks in the Blue Ridge ecoregion are 20 km × 20 km. The rest are 10 km × 10 km.

frequency distribution (JFD) table (Liu et al., 2004a, 2004b). A JFD case contains one or multiple, homogeneous, connected or isolated land pixels, representing a unique combination of the values from the environmental GIS layers used in an overlay operation (i.e., land cover maps of five dates, soil polygons from the U.S. State Soil Geographic (STATSGO) database, atmospheric nitrogen (N) deposition, monthly precipitation, monthly maximum and minimum temperature, and county boundary). Each JFD case has a specific spatial location and extent. The land cover type in a JFD case may change for successive time periods. For instance, a forestland can change to a cropland, or a cropland can change to an urban area. Each forest JFD case was further sub-divided into expanded (or sub) JFD cases to account for selective cutting and additional clear cutting that were not captured in the land cover change maps. Some details about the expansion are given in Section 2.3.

The underlying ecosystem biogeochemical model in GEMS is the Erosion–Deposition-Carbon-Model (EDCM) of Liu et al. (2003), which was modified from the CENTURY model (Parton et al., 1987). For each JFD case, GEMS prepares a set of temporary input data for each EDCM simulation. These input data and parameters include land cover type, climate conditions, soil properties, forest age, crop types, and some land use specifications such as fertilization, crop rotation, crop harvesting, forest selective cutting, and so forth. Some of these input data are generated by Monte Carlo randomization. For example, initial forest age is based on the state level forest age class structure derived from the Forest Inventory and Analysis (FIA) database. Multiple EDCM model runs are performed for each JFD case to incorporate the uncertainty of input data. Model simulated results for the JFD cases are then aggregated to sampling block and ecoregion levels. The GEMS conceptual framework is shown in Fig. 2.

2.3. Forest clear cutting and selective cutting

We do not have continuous FIA related historical forest clear cutting and other stand-replacing disturbances data in GIS format for the study region and for the time period of the study. We obtained the stand-replacing information from the U.S. Land Cover Change Project, in which forest clear cutting and other stand-replacing disturbances can be captured with two consecutive land cover maps derived from remote sensing observations. Because of the fast recovery of spectral reflectance after reforestation, a clear-cutting site, immediately followed by reforestation, might still be classified as a (young) forest land after several years of plant growth. In this situation some clear cuttings might not be recorded in the land cover change maps. An effective time frame of 5 years was defined as the time length that the land cover change maps can trace back the clear cutting events. (Five year is based on the classification method of the land cover change project, where the classification is focused on national level and conservative.) If a site is identified as a forest cutting site on the land cover

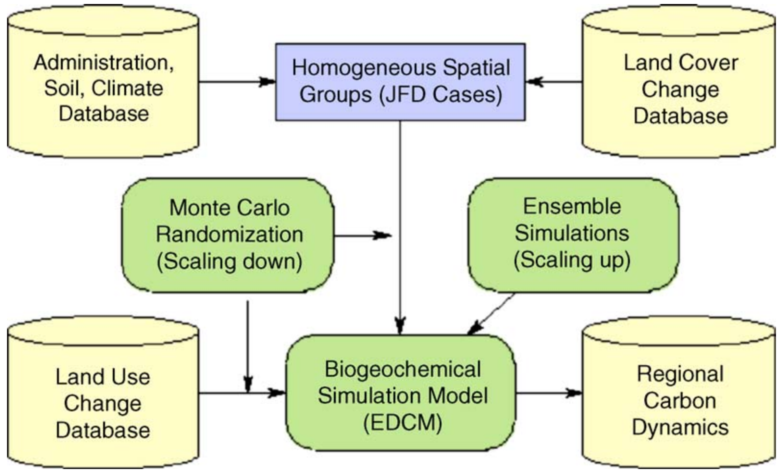

Fig. 2. GEMS flowchart. The process includes Monte Carlo data initializations and ensemble simulations that assimilate the land cover change and other environmental factors into the biogeochemical modeling system.

map, then we set the clear cutting event randomly between the remote sensing date and 5 years prior to that date. If the time period between two consecutive remote sensing observations is longer than the 5-year effective time frame, additional clear cutting events were scheduled following Liu et al. (2004a) by assuming that the annual clear cutting rate detected by remote sensing (i.e. all clear cutting recorded divided by 5) can be applied to the time period outside of the effective time frame. Forest selective cutting is usually not detectable by remote sensing. GEMS prescribed the selective cutting by using the state level FIA data. A forest JFD case was expanded to several smaller cases according to FIA selective cutting information and an expanded JFD case (area equal to the selective cutting portion) was clear-cut.

2.4. The Monte Carlo initialization and outputs from ensemble simulation

Downscaling some information (forest age, soil property) to a detailed level is needed for biogeochemical model parameterization. This was accomplished with a Monte Carlo technique. For example, we need forest age for determining initial forest biomass. The downscaling is to assign a forest age to an individual JFD case based on statewide forest age distribution derived from FIA data, which means a specific forest age class is more likely to be selected if the age class occupies a bigger area.

However, because the current FIA forest age distribution data represents a specific period of time (e.g., North Carolina, 1984), which usually does not coincide with the start year of model simulation (i.e., 1972), we needed to reconstruct the initial age distribution in the start year. Several retrospective rules were applied here:

1. For a given JFD case, if the initial land cover was not forest, then there is no need to assign a forest age. If it becomes a forest later, GEMS assigns an initial age of 1 year when the conversion occurs.
2. If the initial land cover observation was forest, an initial forest age is given. Suppose the FIA observation time is $T_{\rm fia}$, the simulation start time is $T_{\rm start}$, and suppose the Monte Carlo generated forest age at $T_{\rm fia}$ is $A_{\rm fia}$, then the initial forest age, $A_{\rm start}$, is calculated using Eq. (1). If $A_{\rm start}$ is negative, the Monte Carlo process is repeated until it becomes positive

$$A_{\rm start} = A_{\rm fia} - (T_{\rm fia} - T_{\rm start}), \quad A_{\rm start} > 0 \tag{1}$$

3. If a stand-replacing disturbance happened before FIA observation, we assume it was a harvesting and we know that usually the forest was at least 20 years of age at the time of cutting. Suppose the cutting time is $T_{\rm cut}$, and the random age at the cutting time is $A_{\rm cut}$, then $A_{\rm start}$ is calculated using Eq. (2). If $A_{\rm start}$ is negative, repeat the random process until it becomes positive

$$A_{\rm start} = \max(20, A_{\rm cut}) - (T_{\rm cut} - T_{\rm start}), \quad A_{\rm start} > 0 \tag{2}$$

Because of the Monte Carlo process, it is necessary to do ensemble simulations of each expanded JFD case to incorporate the variability and uncertainty of input data and to get unbiased C estimates and the associated variation (Reiners et al., 2002; Liu et al., 2004a, 2004b). Our modeling experiment indicates that for each JFD case the means and standard deviations of output variables can be stabilized with 20 ensemble simulations. Twenty ensemble simulations also produce stable outputs for each sampling block and the whole ecoregion.

2.5. Estimation of C sources and sinks

In this study, the simulations of C stocks and C fluxes in forest ecosystems used the EDCM (Liu et al., 2003). The estimation of forest net primary productivity (NPP) required setting up a maximum potential NPP parameter. This parameter was automated using the Moderate Resolution Imaging Spectro-radiometer (MODIS) product (Heinsch et al., 2003; see http://www.ntsg.umt.edu/modis/MOD17UsersGuide.pdf). The MODIS NPP product provided a good reference for controlling the spatial variation of GEMS NPP output. Each land pixel on the MODIS NPP map had a NPP value. Within each sampling block, we calculated the average of the MODIS top 10% NPP values and used it to derive the potential (maximum) forest NPP parameter for the block. The calculated GEMS average NPP was not the MODIS average NPP, but they were similar in spatial pattern because the GEMS NPP was partly controlled by the MODIS top 10% NPP values. The net ecosystem productivity (NEP) was calculated as the NPP minus CO_2 emissions from litter and soil. NEP accounts for the net C change of an ecosystem before disturbances, which is the same as the net ecosystem exchange (NEE). Because no data were collected for fire and other disturbances in this study, we only specify forest harvested wood C (HWC) removal (representing all stand-replacing disturbances) for the C budget calculation. The net biome productivity (NBP) was calculated as NEP minus annual HWC removal. CO_2 emission from the HWC pool was also calculated. The starting HWC pool was initialized using the assumption that the HWC pool size in the 1970s was 80% of the pool size of HWC of 1990s, according to the temporal change of HWC stocks at the national scale (Skog and Nicholson, 1998). More information on the treatment of HWC was given in Liu et al. (2004a). Different soil C pools have different decomposition rates and influence the C source and sink. Since less information about the fractions of soil slow C and passive C was available, we initialized slow and passive C pool at a proportion of 1:1 after model test for the study region. Fast soil C pool was initialized at 5% of total soil C pool. For each sampling block, NBP was aggregated from the JFD cases. For the whole study region, NBP and its standard variation range were calculated based on the 82 sample blocks. The LUCC impact on forest C flux estimates was related to forest harvesting activities, the changes of forest area, and forest age distributions. In this study, carbon dynamics in the region were simulated separately using the 1972 land cover alone, representing the static land cover scenario, and the 1972–2000 dynamic land cover scenario. The differences of these two simulations were used to assess and quantify the LUCC impacts on carbon stocks and fluxes.

2.6. Data sources

The high-resolution LUCC information was developed using Landsat MSS and TM data (Loveland et al., 2002). Soil coverage data were obtained from the STATSGO database (USDA, 1994) and its initialization approach was outlined in Liu et al. (2004a). Climatic coverages were derived from the United Kingdom's Climatic Research Unit 0.5° data set (CRUTS version 2.0) (Mitchell et al., 2004; Mitchell and Jones, 2005). The total atmospheric nitrogen deposition from wet and dry sources was gathered from the National Atmospheric Deposition Program (http://nadp.sws.uiuc.edu/). Other land use data were collected from sources that included the FIA database and the National Resources Inventory (NRI) database developed by the Natural Resources Conservation Service, U.S. Department of Agriculture. (http://www.nrcs.usda.gov/technical/NRI). MODIS NPP data were downloaded from the University of Montana (ftp://ftp.ntsg.umt.edu/pub/MOD17).

3. Results

3.1. Major land cover changes of the Appalachians from 1972 to 2000

The landscape of the Appalachian region has been altered by logging, urban development, agriculture, and mining. In general, based on the 82 sampling blocks, the Appalachian forestlands (including disturbed land that had been deforested and then reforested) had a net decrease of only about 1% from 1972 to 2000. The major characteristics of LUCC are the urbanization in the BR and RV regions and the conversion of forestland into mining and grassland (reclaimed mine land) in the CA region. Table 1 shows that forest and transitional area in the BR region decreased 0.6% with a 1.2% urban area increase; the RV forest and transitional area decreased 1.4% and agricultural land decreased 0.7% with a 1.4% urban area increase; and the CA forest and transitional area decreased 2.5% with a 1.1% grassland increase and 1.3% mining area increase. These land cover changes were assimilated into GEMS for C simulation. It should be mentioned that only some of the earliest land cover change observations were in the nominal year 1972. In fact, most observations used imagery for 1973, 1974, and even 1975. We assumed static land cover (no clear cuttings) on each sample block before their first land cover observation time.

3.2. Simulated forest ages, C stocks, and C sinks

During the 29 years of the simulation period, average forest age increased 16.1, 20.4, and 19.3 years in the BR, RV, and CA regions, respectively (Fig. 3A). Because of forest removal (mature trees removed and young trees planted), the average

Table 1
Major land cover changes (percentage) in the Appalachians from 1972 to 2000

Ecoregion	Year	Urban (%)	Mining (%)	Forest (%)	Transitional (%)	Grass/shrub (%)	Agriculture (%)
Blue Ridge (BR)	1972	6.0	0.0	83.1	0.0	0.1	10.3
	2000	7.2	0.0	81.8	0.7	0.1	10.3
Ridge and Valley (RV)	1972	7.9	0.2	57.3	0.0	0.1	31.2
	2000	9.3	0.3	55.8	0.1	0.1	30.5
Central Appalachians (CA)	1972	3.3	1.9	86.3	0.0	0.7	6.4
	2000	3.6	3.2	83.4	0.4	1.8	6.8

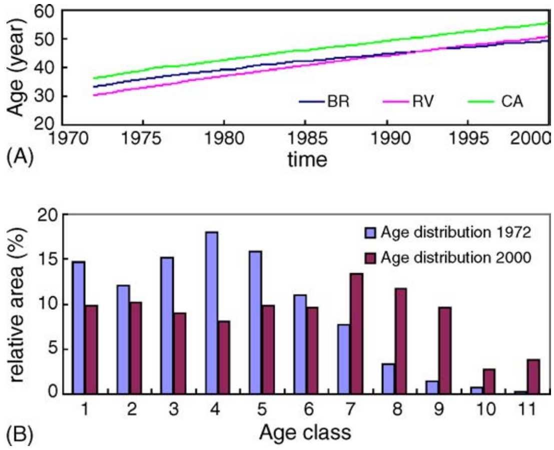

Fig. 3. Estimated average forest age of the Appalachian forests. (A) Forest age increase trends through 1972–2000; (B) forest age class structure in 1972 and 2000 (age class interval = 10 years).

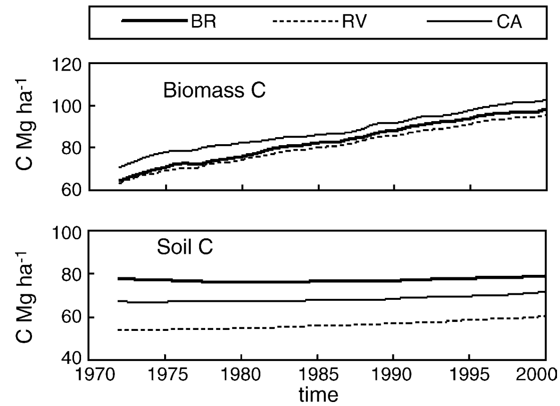

Fig. 4. Estimated historic biomass and soil carbon stocks of the Appalachian forests.

forest age increase for the entire Appalachian was about 0.5–0.7 years per annum. The BR region seemed to have experienced heavier disturbances than the other two ecoregions as shown by the lowest average forest age increase. But the smallest forest area decrease was in the BR, indicating a more active reforestation practice following cutting. If no forest regeneration followed clear cutting, the land would be no longer categorized as forest, so the average age of the remaining forests cannot be deduced by the cutting. The CA region had a greater rate of forest area decrease than the RV region, so it would be reasonable to assume that forest age increase in CA is lower than that in RV. However, the difference in age increment is not big (RV, 20.4 and CA, 19.3). Some forestland may have been converted to mining sites instead of proceeding to forest regeneration, and these mining areas were excluded from the forest age calculation. Normally, older forests would have lower age increases than younger forests if they underwent the same level of disturbance and regeneration. Since the average forest age in CA was higher than that of RV and they had similar age increases, we speculate that RV had relatively heavier disturbance than CA. Here the disturbance means clear cutting followed by forest regeneration. However, the LUCC conversion from forest to other uses (mining in this case) is higher in CA than in RV, indicating fewer reforestations in CA. At the end of the simulation, the GEMS estimates of average forest age agreed with the recent U.S. forest facts that average forest age in the east is about 40–50 years old (USDA Forest Service, 2000). This is because we initialized the forest age based on FIA data and estimated clear cutting rates from remotely sensed data. Fig. 3B shows a typical age class shift in the Appalachian forests. The data is from a sample block in North Carolina. The peak of age distribution fell between 30 and 40 years in 1972, but it hit between 60 and 70 years in 2000. The percentage of old trees (100+ years old) also increased. The age class change was closely related to the woody encroachment discussed later.

The three ecoregions all showed increasing biomass and soil C stocks for the period from 1972 to 2000 (Fig. 4). Biomass C density in the BR, RV, and CA ecoregions increased from 64.3 to 98.1 Mg C ha^{-1} (net change 33.8), 63.4 to 95.3 Mg C ha^{-1} (net change 31.9), and 70.9 to 102.8 Mg C ha^{-1} (net change 31.9), respectively. This also generally corresponds with the FIA data on growing stock volume per hectare in the eastern United States indicating a biomass increase of about 35% from 1970 to 1997 (USDA Forest Service, 2000). None of the three ecoregions showed trends toward biomass equilibrium. Increments of soil C density in those ecoregions were 78.0–78.6 Mg C ha^{-1} (net change 0.6), 53.9–60.2 Mg C ha^{-1} (net change 6.3), and 67.1–71.4 Mg C ha^{-1} (net change 4.3), respectively. The regions with higher soil C stocks had less soil C accumulation. Compared to the biomass C increase, soil C accumulation was very slow. Soil C in both the BR and CA regions decreased or remained stable in the first half of the simulation period and started to accumulate in the later half of the simulation period. This could be due to the younger forest at the start time (indicating heavier disturbances in the previous decade), so the forest produced less C input to soil than soil C loss from respiration. Then the forest gradually became more mature and produced more C input to soil, so that soil C was recovering from previous depletion. The RV region has the lowest forest biomass and soil C stock density. However, RV soil C did not show any decrease in the beginning periods and its net C increase was the highest. This seems partly related to the initial soil C stock level.

NPP is a critical component for our C budget calculation. Fig. 5 shows a comparison of GEMS average NPP and MODIS average NPP (not the NPP of the top 10% high NPP pixels) in the 82 sampling blocks. There is a general correspondence between the two NPP estimates, which showed the effectiveness of using the MODIS top 10% high NPP pixels to control the spatial pattern of GEMS NPP. The scattered distribution of comparison points in Fig. 5 ($R^2 = 0.63$) is mostly due to differences in land cover classification methods, map resolution (GEMS 60 m, MODIS 1 km), and NPP algorithms. In sample blocks where non-forest area was high, the NPP estimates from GEMS were usually lower than the NPP estimates from MODIS.

The historical trends of four major C fluxes (NPP, NEP, C removal, and NBP) are shown in Fig. 6. NPP values in the BR, RV, and CA regions were averaged 6.7, 5.8, and

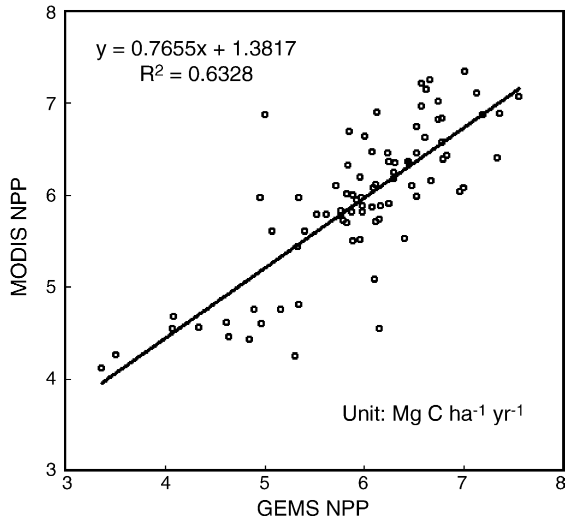

Fig. 5. NPP comparison between GEMS and MODIS at the sample block scale. Each point represents a sample block.

6.1 Mg C ha^{-1} y^{-1} through 1972–2000, respectively. The observed relationship between simulated soil C stock and NPP is consistent with our expectations that higher soil C stocks are usually associated with higher decomposition and thus may lead to higher soil fertility and higher NPP values. BR is the most productive region in terms of NPP, whereas RV is the least productive region. NEP values in those ecoregions were quite similar, about 2.2 Mg C ha^{-1} y^{-1}, and roughly 35% of NPP values. In the BR, soil respiration was high partly due to its higher soil C content and this offset more C from NPP. As for forest C removal, BR had the highest C removal disturbance,

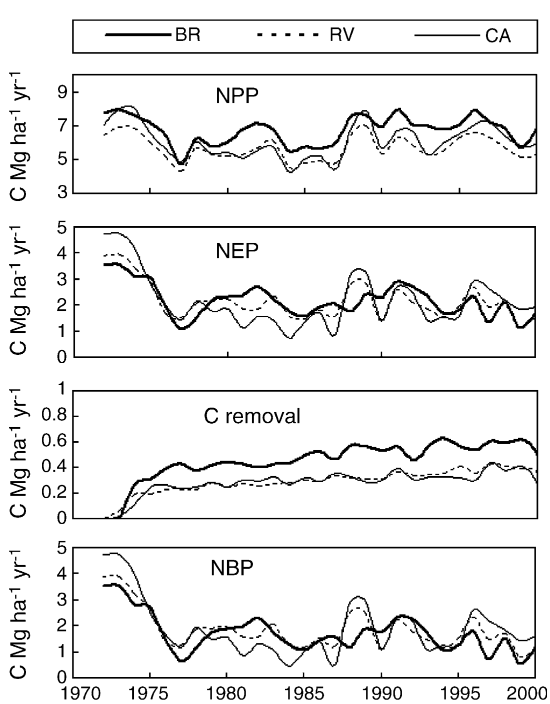

Fig. 6. Historic NPP, NEP, carbon removal, and NBP in the three Appalachian ecoregions.

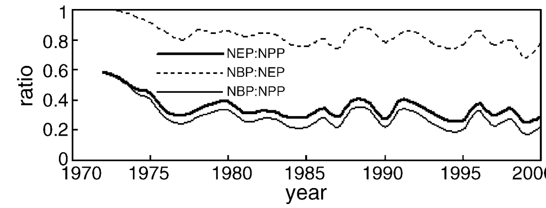

Fig. 7. Selected ratios of NBP, NEP, and NPP in the Appalachian forest ecosystem.

which averaged 0.4 Mg C ha^{-1} y^{-1}, nearly 1.5 times the C removal strength of the RV and CA. NBP (the net C sink) in the three ecoregions averaged 1.7, 1.9, and 1.9 Mg C ha^{-1} y^{-1} for BR, RV, and CA regions, respectively. This was mostly because the BR region had higher soil respiration and C removal. The three ecoregions showed similar NPP and NEP inter-annual variations, which could be more than 1.0 Mg C ha^{-1} y^{-1} resulting from their similar climate histories. The C removal inter-annual variations were usually under 0.2 Mg C ha^{-1} y^{-1}. This indicates that climate variation is the main driving force of NPP and NEP temporal variation in the Appalachians for the study periods.

Combining output data for the three ecoregions (forestland only) in 2000, the averages of NPP, NEP and NBP were 6.2, 2.2, 1.8 Mg C ha^{-1} y^{-1}, respectively. The ratios of NPP:NEP:NBP are indicators of ecosystem production efficiency. Fig. 7 shows that the ratio of NEP:NPP is about 0.3–0.4, i.e. approximately 60–70% of the NPP product was respired from soil and litter as CO_2. The ratio of NBP:NEP is 0.8, which means only 20% of the ecosystem C accumulation was removed from the system by human disturbances.

Based on the 82 sampling blocks, the mean and variance of NBP in the Appalachian forests were calculated. The simulated NBP varied from 1.0 to 2.7 Mg C ha^{-1} y^{-1}, with a mean of 1.8 Mg C ha^{-1} y^{-1}. The standard deviation ranged from 0.7 to 1.2 Mg C ha^{-1} y^{-1}, with a mean of 0.9 Mg C ha^{-1} y^{-1}. NBP estimation at the 95% confidence level is shown in Fig. 8. Estimated NBP in 1972 and 1973 was high because our baseline land cover change observations were mostly started in 1973 and 1974 (few were in 1972 and 1975). So, the majority of forest removal (harvesting) happened after 1975 in the model.

The net C sequestration in the region can be attributed to three pools: biomass, soil, and HWC. Fig. 9 shows the relative C accumulation strength of three pools for three time periods.

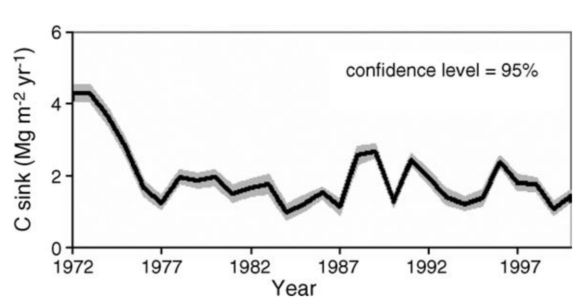

Fig. 8. Simulated carbon sink dynamics (NBP) of the Appalachian forests with standard errors calculated across blocks for each year based on the 82 sampling blocks.

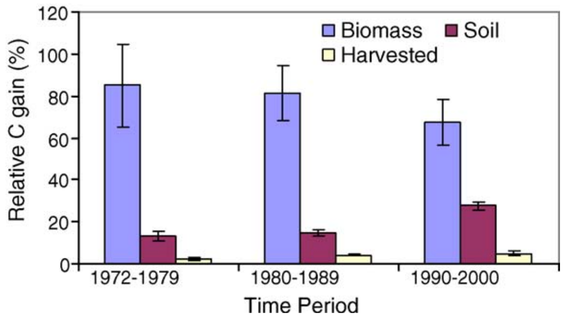

Fig. 9. Relative allocation of net carbon gains to biomass, soil and harvested carbon pools in the past decades.

In the early period of the simulation, about 80% of the sequestered C accumulated in the biomass pool. However, as the simulation continued the relative biomass C accumulation decreased and the C accumulation in soil and harvested wood pool increased. This may reflect the LUCC in the past few decades (1972–2000) because higher biomass C accumulation at the beginning of simulation years indicated younger forests and disturbed soil, and less intensive harvesting at a later stage made the forest grow mature, and more C went into soil C pools.

3.3. C budget of 2000

Some major Appalachian forest C stocks and fluxes in 2000 are provided in Table 2. The ratio of biomass C to soil C is estimated to be 1:1.1. The ratio of NPP:NEP:NBP is estimated to be 100:29:23. The harvested C is only about 6% of NPP and 21% of NEP. It shows that the RV ecoregion had the least biomass and soil C density and the lowest NPP and NEP compared to the other two ecoregions in 2000. The BR ecoregion had the highest NPP, and at the mean while, the highest C removal. The CT ecoregion had the highest NEP and NBP.

Fig. 10 shows detailed budgets of the simulated C pools and fluxes of five biomass components, three litter components (including standing dead wood, above-ground litter and below-ground litter) and three soil components of the Appalachian forests in 2000. The total NPP was estimated at 86.7 Tg C y^{-1}, of which 16.6 Tg C was stored in living plant biomass; 5.3 Tg C was removed to the harvested wood pool; and 64.8 Tg C went into litter pool. About 61.3 Tg C was released into the atmosphere through soil and litter decomposition. Net litter and soil C increments were −1.6 and 4.4 Tg C, respectively. The net litter loss was caused by the decomposition of the relatively high level of litter in the previous year. (Some litter, such as leaf, decomposes fast. A high production year will produce high level of litter stock, but if followed by a low production year, the litter stock will be lowered.) The NEP of the overall forest ecosystem was 24.8 Tg C y^{-1}, and NBP (i.e. NEP, removal) was 19.5 Tg C y^{-1}, indicating the Appalachian forest ecosystems were a net C sink in that year. As for the harvested wood C pool, a wood product decay amount of 7.1 Tg C was lost in 2000, but a new harvesting wood C of 5.3 Tg was added to the pool. Therefore, the net change of harvested wood C pool was −1.8 Tg.

3.4. Evaluation of land cover change impact on C sequestration

We simulated the sample blocks of the BR region using a single land cover map (1972–1975) and compared the results with a simulation using five dates of land cover maps. Fig. 11 shows that without dynamic LUCC, the simulated NBP for the BR region would be higher than the sum of the simulated NBP plus the C removal under a dynamic LUCC scenario. The difference was from the increment of forest growth that was simulated in the static modeling scenario but did not occur in the dynamic modeling scenario. The simulation with land cover change was about 10–20% less than the simulated C sequestration under static LUCC for this study.

4. Discussion

Parameterizing biogeochemical model using remote sensing product is helpful. The spatial pattern of GEMS NPP generally matched the MODIS estimates because GEMS initialization used MODIS high NPP values. However, at sites with a high proportion of non-forest land, GEMS forest NPP estimates were usually lower than MODIS NPP estimates. This could be due to the differences of land cover classification, map resolution, mixed pixels, NPP algorithms, or other factors. Using MODIS NPP to control the GEMS NPP calculation is still empirical. There are other options for improving the GEMS NPP sub-model in the future, such as importing NPP maps from other biogeochemical models and importing physiological NPP algorithms.

The biomass estimation of GEMS is higher than the FIA state level average. This may be caused by a number of things: GEMS does not consider stem density, forest cover fractions,

Table 2
Carbon stocks density and fluxes of Appalachian forests in 2000

Ecoregion	C stocks			C fluxes			
	Total C	Biomass	Soil	NPP	NEP	NBP	Harvest
Blue Ridge (BR)	196 (±18)	98 (±3)	98 (±15)	6.8 (±0.7)	1.7 (±0.5)	1.2 (±0.5)	0.5 (±0.3)
Ridge and Valley (RV)	174 (±19)	95 (±12)	79 (±11)	5.3 (±1.3)	1.5 (±0.8)	1.2 (±0.8)	0.4 (±0.3)
Central Appalachians (CA)	196 (±13)	103 (±13)	93 (±8)	6.0 (±0.7)	1.9 (±0.5)	1.6 (±0.5)	0.3 (±0.2)
Appalachian Average	186 (±20)	98 (± 2)	88 (±13)	5.9 (±1.1)	1.7 (±0.6)	1.3 (±0.6)	0.3 (±0.3)

Data in the parenthesis are the standard deviations. Units: Mg C ha^{-1} for C stocks, and Mg C ha^{-1} y^{-1} for C fluxes.

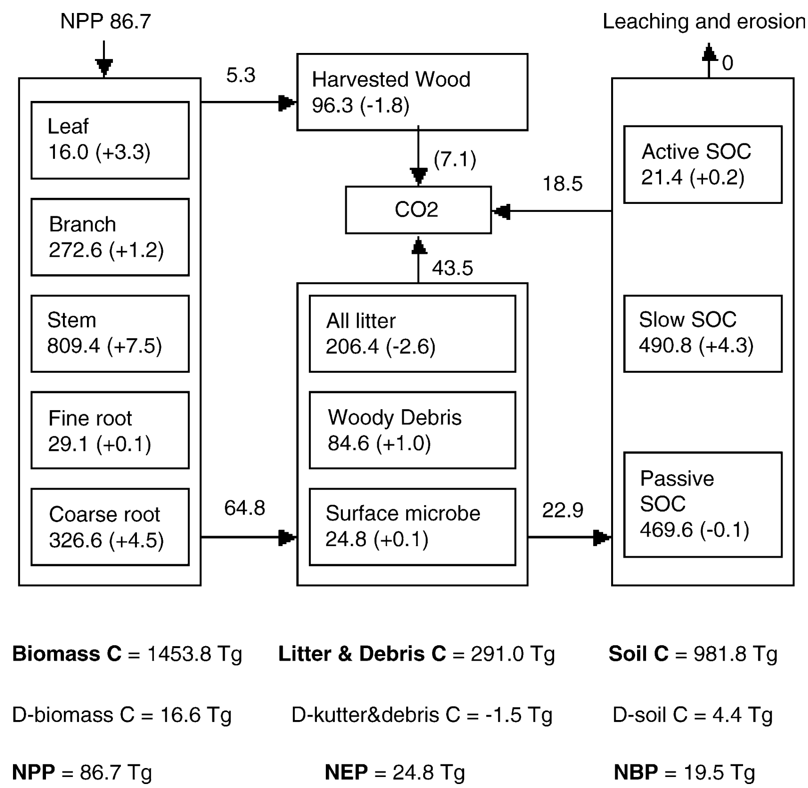

Fig. 10. Detailed carbon budget of Appalachian forests in 2000 (unit: Tg C). Each ecosystem component is labeled with name, carbon pool size at the end of the year and carbon change rate. SOC: soil organic carbon. D: net change rate. "Harvested Wood" is a virtual offsite carbon pool based on Liu et al. (2004a).

and tree species whereas the FIA data accounts for all types of forests including sparse forests. In addition, we used only state level averages of the FIA data. Since the Appalachian region is more productive than the surrounding areas and the selected ecoregions cover only part of each state, the higher biomass estimation than FIA is not unreasonable, although the accuracy still needs further evaluation.

Details of the C budget in 2000 provided further validation of the GEMS outputs. The ratio of live belowground biomass C to total live biomass C is 0.24, which matches the FIA analysis (0.25) of Johnson and Sharpe (1983). This estimation is also close to the estimation of Jenkins et al. (2001), according to

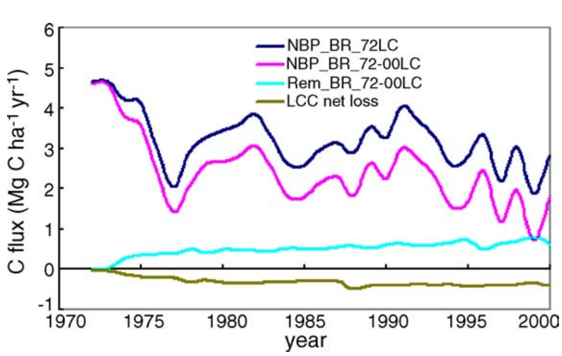

Fig. 11. Simulated impact of LUCC on C sinks in the Blue Ridge (BR) ecoregion. Without dynamic LUCC introduced into GEMS, the C sink strength for the BR region would be higher. This static LUCC based NBP value was higher than the sum of the NBP under the dynamic LUCC scenario plus the actual C removal. The estimated net C difference induced by LUCC was about 10–20% of the simulated C sink under dynamic LUCC.

which the coarse root (not including fine root) to total wood ratio is about 0.2. The aboveground litter is 17.6% of the total aboveground biomass, which is slightly higher than the estimated range of 4–17% of Johnson and Sharpe (1983). The higher litter output may be caused by the model parameterization in which no litter is removed and no fire disturbance event is simulated. This issue can be resolved when proper fire regimes and litter removal are prescribed in GEMS.

Estimated NBP of Appalachian forests from 1972 to 2000 is 1.8 Mg C ha^{-1} y^{-1} (±0.6). This estimate is higher than the results of Hurtt's et al. (2002), where their estimated forest C sink strength in the 1980s for all the United States was about 0.9 Mg C ha^{-1} y^{-1}. The high C sink strength was partly because of the forest woody encroachment during 1970–2000. This can be verified by comparing the biomass C sink to soil C sink ratios of GEMS result (80:20) and Hurtt's result (45:55). The estimated NEP of Appalachian forests is 2.2 Mg C ha^{-1} y^{-1} (±0.6). This value is close to Brown and Schroeder's (1999) estimation of 2.1 Mg C ha^{-1} y^{-1} for the forest in the eastern United States. It is also close to the estimation of 1.4–2.8 Mg C ha^{-1} y^{-1} for the mature forests in New England (Goulden et al., 1996).

For the Appalachian forests, the ratios of NPP:NEP:NBP in 2000 are estimated to be 100:29:23. High NEP may indicate that the Appalachian forest ecosystem had high growth (NPP) and low mortality due to the young forest age. High NBP indicates that human disturbance (harvesting removal) was reduced. In fact, forest harvesting in the Appalachian region in 2000 (5.3 Tg C) was only 21% of NEP (24.8 Tg). From the simulation, most of the C sequestered (about 70–80%) was stored in biomass. So the C sink was mainly a woody encroachment phenomenon, which can also be verified by the changes of forest age class structure.

The average soil C sink was estimated about 0.1 Mg C ha^{-1} y^{-1} during the 1980s, which was at the lower limit of the estimates of Gaudinski et al. (2000) that temperate forest soils sequestrated 0.1–0.3 Mg C ha^{-1} y^{-1} during the same time period. This was probably due to the low litter input and low mortality at stand level when the forest was young. However, the BR region had the highest soil C stock but the lowest soil C increment. The reason was most likely the heavier disturbance and the related stand age dynamics at regional level. BR region had about doubled harvesting intensity than the other two regions. So more forest land had been disturbed and the regional soil C increase was lower. It is likely that forest (mainly biomass pool) in this region will be a net C sink for several decades to come because of its current age and harvesting intensity.

Some ecosystem features are scale-dependent. Net C change in a small region could be positive or negative and more dynamic than large regions. When C source and sink values from sub-regions are averaged and smoothed for larger regions, the regionally averaged C trend is more stable than at the stand level. Regional level average forest age is another scale-dependent feature. It is apparent that the regional average forest age is an indicator of historical disturbance because the forest age increment per annum is smaller than one. A smaller age increment reflects heavier disturbance.

This study has been based on dynamic LUCC history. At present, this type of LUCC history is available only for the sampling blocks. We have calculated the carbon balance at high resolution for the sample blocks, but at the ecoregion level it is not yet spatially explicit. Various strategies can be exploited to quantify the spatial distribution of this C sink, including GIS interpolation, regression tree and neural networks.

The impact of land cover change on C sequestration includes the adjustment of forest growth. When a forest is removed, the potential growth is also removed. Comparison of the estimated C sinks under static and dynamic land cover revealed that a reduction in C accumulation could be caused by the removal of ‘‘growth’’. For the BR region, this reduction was about 10–20% of NBP.

Acknowledgments

We sincerely thank Norman Bliss for his comprehensive and final revision on this manuscript. We also thank Bruce Wylie and the three anonymous reviewers for their very valuable comments and suggestions. This study was supported by sources from NASA Earth Science Enterprise (grant no. LUCC99-0022-0035), the U.S. Environmental Protection Agency (DW14938108-01-0), and U.S. Geological Survey (Geography Discipline Research Prospectus Project ‘‘Contemporary terrestrial carbon sources and sinks in the conterminous U.S.’’, and the Earth Surface Dynamics Program). S. Liu's work was performed under U.S. Geological Survey contract 03CRCN0001. J. Liu was supported by an award from the Research Associateship Program of the National Research Council via an agreement with the U.S. Geological Survey.

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